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Research Article

Improved Grey Wolf Optimisation-Based Feature Fusion Deep Neural Network for Chest Disease Detection

Maneet Kaur Bohmrah[1], Harjot Kaur[2]

[1,2]Department of Computer Science and Engineering Guru Nanak Dev University, Amritsar, India.
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Corresponding Author:
Maneet Kaur Bohmrah, Department of Computer Science and Engineering Guru Nanak Dev University, Amritsar, India.
E-mail Id:
maneet.2009@gmail.com
Orcid Id:
https://orcid.org/0000-0003-4389-3497
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ABSTRACT

Introduction: Automated diagnosis of COVID-19 is an emergent need in the domain of medical image analysis. COVID-19 is an obstructive pulmonary disease and its common symptoms include cold, fever and cough. COVID-19 is a communicable disease and due to its transmissible characteristics, it rapidly transfers and affects a large number of populations. Conventional analysis of chest X-ray (CXR) images plays a significant role in the detection of abnormal lung regions, but it is a time-consuming and complicated task to examine CXR images of thousands of COVID-19 patients for a radiologist. Consequently, there is a requirement of a fast, accurate, and reliable computer-aided diagnosis system (CAD).

Method: The primary goal of this study is the selection of the most prominent features of input CXR images to improve classification accuracy. Metaheuristic algorithms are always the best choice for solving the issue of feature selection. In order to obtain the optimal feature subset from the extracted deep ResNet50 and MobileNetV2 features set, a dimension learning hunting-based Grey Wolf Optimisation (GWO) algorithm has been proposed in this study.

Results: Experimentation work shows that IGWO selects minimum 823 features and using these features the obtained COVID-19 image classification accuracy is 98.78% which is comparatively more than the accuracy obtained in case of PSO(98.47%) and GWO(97.78%).

Conclusion: The obtained results indicate that the Improved version of GWO provides better classification accuracy as compared to the other original versions of GWO and Particle Swarm Optimisation (PSO) feature selection algorithms

Keywords: Deep Neural Networks, Metaheuristic Algorithm, Feature Selection, Machine Learning, COVID-19

Introduction

COVID-19 (also called coronavirus) is an acute pulmonary disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Some of the common symptoms observed among COVID-19 patients are cough, cold, fever, body ache, and chest blockage. It is a communicable disease as soon as an individual comes into contact with the infected person it gets transmitted. Owing to its transmissible characteristics, it has become uncontrollable despite several preventive measures taken by the government to combat this virus. At the worst, this virus spread rapidly in the form of various variants such as omicron and many more.[1,2] The most commonly used method for COVID-19 detection is Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR), widely regarded as the gold standard due to its high sensitivity and specificity. However, RT-PCR can be time-consuming and may be affected by practical challenges, such as the need for manual processing and sample handling, which can introduce variability in results, especially in high-demand settings. Moreover, the disease detection rate is comparatively lower than the rate at which it spreads and affects human life. Considering the high number of COVID-19 sufferings, it become imperative to use contemporary techniques, such as Artificial Intelligence (AI) in order to prevent more suffering with a timely diagnosis of the disease.[3]

Medical imaging technology plays an important role as a diagnostic tool in the design and development of computer-aided systems. To detect non-invasive possibilities in the human body, a variety of proficient medical imaging systems such as MRI, PET, Endoscopy, CT scan and Chest X-rays (CXRs) have been used, which can capture images of the inner infected parts of various organs of the human body. Chest radiography and computed tomography (CT) are the two most commonly non-invasive and painless examinations that contain vital information regarding the presence of abnormalities within the lungs. CXRs are preferable due to their ease of availability at an affordable cost. However, manual screening of these images is a time-consuming process and has more chances of retaining erroneous results. Therefore, it is essential to develop automated AI-driven systems to achieve accurate and rapid results. The goal of this study was to combine the benefits of two modern technologies, medical imaging systems and artificial intelligence as a resultant 'medical AI'.[4]

For disease detection, machine learning, deep learning models and the hybridisation of these two techniques have been proven to be powerful automated disease detection tools, and they have been recently employed in the detection of various diseases such as COVID-19, brain tumour, monkeypox, and diabetic retinopathy. On the other hand, literature has known innovations for feature extraction techniques and multi-feature extraction or hybrid feature extraction approaches based on DNNs. Most of the research studies have shown deep neural networks (DNNs) as a successful feature extractor tool. Extracted features were further used by the machine learning classification models for the accomplishment of the classification task. Most of the studies discussed the issues that arise due to the large dimension extracted feature set which is the result of hybrid feature extraction. Multi-level feature extraction or hybrid feature extraction is the process where extracted features of more than one DNN have been combined together to form a large feature set.[5] Previous studies also mentioned that the classification results may be misguided due to the presence of irrelevant and redundant features belonging to the fused feature set. Hence, to overcome these problems, feature selection techniques have been introduced. A few studies have shown the adoption of feature selection for image classification using DNNs. Metaheuristic, nature-inspired algorithms have been preferred to solve the problem of feature selection.[6,7]

The main goal of this research is to develop a computer-aided diagnosis framework that will accurately identify chest disease with minimal processing time and accurate outcomes in terms of classification accuracy. This prominent research area presents a number of challenges, including the choice of an appropriate technique for improving the quality of images to tackle noisy and low-quality CXR images and the extraction of relevant information. Therefore, strong feature extraction and selection algorithms are required in order to extract meaningful information and filter out the most significant features for the classification of various chest diseases. The proposed framework consists of five major stages such as (a) image preprocessing (b) feature extraction (c) feature selection (d) feature fusion, and (e) classification. The major contributions of this study can be stated as:

- Adaptive image segmentation and enhancement techniques have been adopted to extract meaningful information from the input CXR images.
- Employed standard deep neural networks (DNNs), i.e., ResNet50 and MobileNetV2, for the purpose of feature extraction. Extracted features from both models were fused together to form a large feature set which also increased the reliability of the proposed framework.
- Dimension learning-based grey wolf optimisation has been proposed for the selection of significant

optimal feature subsets. To generalise the algorithm, the outcomes of the proposed algorithm have been compared with other metaheuristics algorithms, namely original GWO and Particle Swarm Optimisation (PSO).

- Selected features are further utilised for the classification task using disparate machine learning classifiers such as Decision Tree (DT), kNN (Nearest Neighbour), Naive Bayes (NB), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM).
- Comparative analysis has been performed with other state-of-the-art methods to prove the validity of the proposed model.

The aim is to leverage the strength of deep neural networks (DNNs), metaheuristic feature selection algorithms and machine learning (ML) classifiers to discover and classify a broad spectrum of chest infections and strongly recommend them as a supporting diagnostic tool for the medical experts to take decisions on disease accurately and in a timely manner.

The rest of the paper is outlined as follows: Section 2 discusses the previous studies related to chest disease and the considered articles basically based on feature selection techniques and deep learning models, Section 3 contains a succinct explanation of the proposed approach, and Section 4 presents the experimental results and discussions. Finally, the paper concludes in Section 5.

Related Work

In the recent past, numerous studies have proposed artificial intelligent systems for the detection of COVID-19 and other chronic chest diseases. This section discusses the various proposed works based on these emerging technologies for the diagnosis of different chest diseases including pneumonia and COVID-19.

Abdullah et al. proposed modified pre-trained DNNs including VGG-16 and VGG-19 and made use of disparate traditional ML classifiers such as Nearest Neighbour, Support vector machine, Random Forest, Naive Bayes and Neural Network for the automatic detection of COVID-19 based on CXR images.[8] Experimental outcomes imparted that among the five ML classifiers experimented in their work, linear SVM attained the highest accuracy score of 92%.

Hossen et al. presented a combined concept of feature selection (FS) and classification algorithms for an effective data mining approach. Different FS algorithms, i.e., chi-square test, Recursive Feature Elimination (RFE), Genetic Algorithm (GA) and PSO were deployed and the selected features were classified using disparate ML classifiers.[9] The proposed model trained on the Israeli COVID-19 dataset based on attribute values (symptoms like fever, cold, cough and sneeze) and achieved an accuracy score of 88.8%.

Shukla et al. utilised the standard pre-trained DenseNet201 model for the purpose of feature extraction and combination of binary sine cosine algorithm and adaptive beta hill climbing for the selection of features and the proposed model attained an accuracy score of 98.92% with SVM classifier.[10]

Kaya et al. presented a novel automatic COVID-19 diagnosis tool, called D^{3}SENet that includes a hybrid feature extractor, selection and classification as the three main components of the model.[11] The Hybrid feature extractor model utilised extracted features from five standard pre-trained CNNs models and they are DarkNet19, DarkNet53, DarkNet201, SqueezeNet and EfficientNetB0. The deep extracted features by the hybrid extraction model were further selected using the Relief FS algorithm. The obtained optimal feature subset was further classified using the SVM classifier. The proposed D^{3}SENet, the three-stage model achieved an accuracy score of 98.78% for the multi-class CXR dataset.

Hussein et al. proposed a lightweight CNN mode with image normalisation and data splitting techniques. Experimental results showed that the proposed model achieved an accuracy score of 98.55% for binary and 96.83% for multi-class classification.[12]

Torse et al. proposed a metaheuristic-based COVID-19 detection model comprised of the Least Square Support Vector Machine (LSSVM) and a modified quantum-assisted marine predictor algorithm.[13] The proposed approach trained and validated using a multiclass COVID-19 dataset (comprised of COVID-19, Normal and viral pneumonia) and obtained an accuracy score of 87.2%.

Nasiri et al. proposed a COVID-19 classification model based on the feature selection method (Analysis of variance (ANOVA)) for the selection of significant features extracted by using a pre-trained DenseNet169 model and classified with the implementation of the XGBoost classifier.[14] Further, the suggested model achieved an accuracy score of 98.72% (for binary classification), i.e., when tested on DS1 comprised of COVID-19 and Normal CXR images and 92% (for multiclass classification), i.e., when tested on DS2 consisted of COVID-19, Normal and Viral pneumonia CXR images.

Kathamuthu et al. experimented with a diverse set of pre-trained DNNs including ResNet50, Xception, VGG16, VGG19, DenseNet121 and InceptionV3 for the detection of COVID-19 using CT scan images.[15] Experimentation work has been that the maximum accuracy score of 98% has been attained by the VGG16.

Goyal and Singh also experimented with the three pre-trained DNN models such as ResNet50, VGG16, and VGG19 using 749 CXR images classified as COVID-19, viral pneumonia and normal images.[16] The findings of the experimentation work showed that the VGG19 attained a maximum accuracy of 98.12%.

Pathan et al. experimented with a diverse set of pre-trained models such as ResNet50, AlexNet, VGG19, DenseNet and InceptionV3 for the feature extraction and two metaheuristic algorithms including whale optimisation algorithm (WOA) and BAT algorithm for feature selection.[17] The proposed model obtained an accuracy of 98% with the Adaboost classifier for the detection of chest disease.

Ozturk et al. presented disparate traditional feature extraction methods (Gray Level Run Length Matrix (GLRM), Gray Level Correlation Matrix (GLCM), and Local Binary Pattern (LBP)) in order to extract features from CT and Chest X-ray images to implement the proposed binary classification COVID-19 detection model.[18] Most significant features (extracted features optimised using the PCA algorithm) were classified using SVM classifier and the proposed model obtained an accuracy of 94.23%.

Numerous studies have shown the adaptability of DNNs as a feature extractor and ML models as a classifier for the accurate detection of COVID-19. Few studies adopted the feature selection (FS) technique as an intermediate stage of feature extractor and classifier to improve the quality of extracted image features and also speed up the computational process of ML classifiers. This study aims to propose an efficient feature selection based on dimension learning grey wolf optimisation for the selection of significant CXR image features.

Preliminaries

This section illustrates the basic terminologies used to formulate the proposed framework for the early diagnosis of chronic chest disease. The proposed “Feature Fusion Deep Neural Network (FFDNN)” has been divided into five major steps and these steps are discussed in the upcoming sections.

Image Preprocessing

Image preprocessing plays an important role in the classification model, mainly for medical images for the removal of unwanted regions or noise patterns.[19] Image preprocessing has been implemented in three major steps which are as follows:

Image Filtration: This technique is responsible for the modification or enhancement of an image by facilitating in removal of different types of noise such as Gaussian, Salt and Pepper, Poisson noise, impulsive and speckle noise.[20] The CXR images which have been used to validate FFDNN are mostly subject to Gaussian, Salt and Pepper, and Poisson noise. These noisy CXR images can be handled using a noise removal filter called the median filter.

$$I_f(x,y) = Med\big(I(x,y)\big) \tag{1}$$

Where Med is a median filter and I_f (x, y) is a filtered and sharpened image obtained after the application of the median filter to the original CXR image I(x, y). Removal of noise patterns further helps in the edge detection method for the process of segmentation.

Image Segmentation: This is responsible for the separation or masking of a meaningful region (also termed the region of interest (ROI)) from an image. In the case of CXR images, the target ROI is the lungs (i.e., both the left and right lung regions). In this study, for efficient ROI extraction, an adaptive edge-based image segmentation technique has been devised as an intermediate and transitional solution.[21] This proposed technique uses Hough Transform-Canny Edge Detection for automatic identification of ROI boundary. With the help of edge detection and morphological operators segmented binary mask has been obtained which is further applied over the original image (Equations 2 and 3).

$$BM(x,y) = edgedetection\big(I_f(x,y)\big) \tag{2}$$

$$BM_{final}(x,y) = Morph\_oper\big(BM(x,y)\big) \tag{3}$$

$$I_{seg}(x,y) = Mask\ (BM_{final}(x,y), I_f(x,y)) \tag{4}$$

where BM(x,y) and BM_{final}(x,y) are binary masks obtained during edge detection and morphological operations (i.e., dilation, fill and erode). The final computed binary mask BM_{final}(x,y) was masked over the filtered image for segmentation, resulting in the final segmented image and I_{seg}(x,y) as extracted ROI.

Image Enhancement: It enhances the contrast of grayscale and coloured images using Contrast-Limited Adaptive Histogram Equalisation (CLAHE). In the case of CXR images, the strong contrast in the white area can wash out vital information carried by the white pixels.[22] To retain this vital information, CLAHE is applied over the segmented image I_{seg}(x,y) (Equation 5) for intensity enhancement, improvement of local contrast, and edge definitions. This process produces a final enhanced segmented image (I_{clahe}(x,y)), which is further used for training the proposed framework.

$$I_{clahe}(x,y) = CLAHE\big(I_{seg}(x,y)\big) \tag{5}$$

The step-wise functional implementation for preprocessing of CXR images has been demonstrated pictorially as in Figures 1a–1h, respectively.

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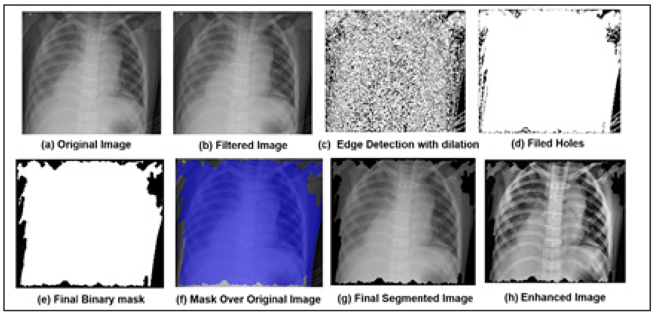

Figure 1.Application of Image Preprocessing Techniques on Raw CXR Images

Feature Extraction

Manual extraction of image features is a cumbersome approach. DNNs are widely used for feature extraction purposes. Due to its complex architecture, thousands of network layers learn the deep features of images such as colour, texture, shape and so on. Convolutional Neural networks (CNNs) are a major type of DNN and are widely used for the image classification task. CNN consists of three primary layers i.e. convolutional layer, pooling and fully connected (FC) layer with some other additional layers (such as Batch normalisation, ReLU and dropout layer). Convolutional layers are the building blocks of the CNN model. This laye r is responsible for convolution operation with filters and performs specific tasks such as extraction of colour, texture, geometric or edge features which in turn performs image feature extraction. The pooling layer is the primary layer of CNN which is responsible for the regulation of dimensions of the input image without loss of any valuable image fature and makes the training process faster. Another vital layer is the FC layer, responsible for the conversion of 2D deep feature maps into 1D. It is also responsible for the accumulation of all the features extracted by the previous layer.[12,23]

This work focuses on the implementation of two standard pre-trained CNN models, namely ResNet50 and MobileNetV2 in order to extract features for accurate chest disease prediction using CXR images. The process of feature extraction defines the second stage of the proposed framework. The implemented feature extractor model has been discussed in further sections.

Mobilenetv2

MobileNetV2 is a pre-trained, 154-layered CNN model widely used for applications such as image classification, pattern recognition, object detection, semantic segmentation, augmented reality, etc. This model can be distinguished from other pre-trained models as it replaces exorbitant convolution layers with depth-wise separable convolutional blocks also known as residual blocks. The complete MobileNetV2 architecture consists of 16 bottleneck blocks preceded by a global average pooling layer and a fully connected layer.

The projection layer, also known as the point-wise layer merges the filtered features to generate new distinct features and reduce the feature map with a higher to lower number of channels. The global average pooling layer with size 1x1x1280 is responsible for performing the function of pooling in MobileNetV2.[24] A total of 1000 features are extracted by “Logits” or fully connected layer for CXR images.

ResNet50

ResNet50 is a pre-trained Convolutional Neural Network (CNN) model and is a variant of the ResNet model also called “Residual Network” with deep 50 layers. ResNet50 is a popular CNN model and widely used model for image classification problems with large datasets. Its residual connections constitute a distinguishable feature which helps the network to grasp residual functions and map the input with the intended output.

The two major components of ResNet50 are convolutional and identity blocks; further, these blocks comprise several convolutional layers followed by batch normalisation and activation function, ReLU. These layers are responsible for capturing features such as colour, shape, texture, and edge information from the input CXR images. Max pooling which is responsible for the reduction of feature dimension without any loss of valuable features is also one of the components of ResNet50.

Identity block also called residual block where input passes through several convolution layers and the output is added with the fed input. This enables the network to acquire knowledge of the residual function and also controls the problem of gradient loss. Moreover, convolutional blocks followed by the identity blocks and much more similar to their architecture, only the additional 1X1 convolution layer to reduce the number of filters is introduced before expensive computation by the 3X3 convolution layer which also speeds up the training process of the model. At last, the 2D Global Average Pooling layer, also called the flatten layer, is responsible for the conversion of the 2D to 1D feature map.[25] A total of 1000 features are obtained using a fully connected layer (“fc1000 layer”).

Feature Fusion

This section introduces the feature fusion process which makes the proposed model more reliable. In this study, extracted features from different pre-trained models, i.e., ResNet50 and MobileNetV2 are serially fused together to generate feature fused sets. The process of serial fusion can be explained as follows: assume f_{ext1} and f_{ext2} are the features extracted from two pre-trained

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CNN models such as CNN_1 and CNN_2. After the process of extraction, the extracted features are fed to the feature fusion layer for the fusion of two extracted feature sets and the process can be defined as Equation 6.

$$f_{fusion} = FUSION\ (f_{ext1}, f_{ext2}) \quad (6)$$

where f_{fusion} is the final version of the feature fusion set and it is the summation of all the features contained by f_{ext1} and f_{ext2}. In this study, extracted features obtained from ResNet50 are represented by f_{ext1} of size N X 1000, whereas MobileNetV2 features are denoted by f_{ext2} of size N X 1000. According to Equation 6 , after the process of fusion, f_{fusion} has been obtained of size N X 2000.

Feature Selection

Feature selection is the process of extracting significant features from the extracted feature set. There are mainly two benefits of feature selection techniques: firstly, it helps in the reduction of large fused extracted feature sets. Secondly, the removal of redundant and irrelevant features from the extracted feature results in an optimal feature subset. Feature selection improves the classification accuracy as well as reduces computational time. Metaheuristic algorithms have been implemented for the feature selection task.[6] In this study, an improved version of grey wolf optimisation has been proposed for the retrieval of the most significant features.

Grey Wolf Optimisation (GWO)

A population-based swarm intelligence metaheuristic optimisation algorithm called Grey Wolf Optimiser (GWO) was proposed in 2018.[26] GWO mathematically simulates the social behaviour, hunting mechanism and dominant leadership hierarchy of grey wolves for optimisation problems. Alpha (α), Beta (β), Delta (δ) and Omega (Ω) are the four types of grey wolves whose grouping hunting behaviour is simulated in GWO. Alpha (α) types are responsible for decision-making and are considered the best solution. They dominate the other beta (β) and delta (δ) wolfs. Beta (β) wolf followed the Alpha (α) and is considered to be the second-best solution and second powerful wolf which may also replace the Alpha (α), if needed. The remaining candidate solutions are considered to be omega wolves. The optimisation process in GWO is accomplished by imitating the group hunting mechanism of these powerful wolves, α, β, δ and Ω wolves can be classified into three major steps: approaching prey, harassing and chasing the prey till it stops moving and attacking. Alpha (α) wolf is considered to acquire better information about the potential position of prey. Grey wolves surround their target during the hunt and this surrounding activity is formulated as defined in Equations 7 and 8.

$$\boldsymbol{D = |C.X_{prey}(iter) - X_{wolf}(iter)|} \quad \textbf{(7)}$$

$$\boldsymbol{X(iter+1) = |X_{prey}(t) - A.D|} \quad \textbf{(8)}$$

Where X_{prey} is the position of prey and X_{wolf} is the position of the grey wolf, iter is the current iteration and iter+1 denotes the next iteration. A and C are real numbers that can be calculated using Equations 9 and 10.

$$A = 2.A.rand_1 - a(t) \quad (9)$$

$$C = 2.rand_2 \quad (10)$$

Where $rand_1$ and $rand_2$ are random values within the interval [0,1] and the element linearly decreases from 2 to 0 with the succeeding iterations as shown in Equation 11.

$$a(t) = 2 - \frac{2t}{T} \quad (11)$$

Hunting mechanism of α, β and δ can be formulated using Equations 12–17 where the leader wolves accumulate better information about the position of prey and another candidate Omega (Ω) follows them.

$$D_\alpha = |C_1.X_\alpha - X(iter)| \quad (12)$$

$$X_1(iter) = X_\alpha(iter) + A_1.\ D_\alpha(iter) \quad (15)$$

$$X_2(iter) = X_\beta(iter) + A_2.\ D_\beta(iter) \quad (16)$$

$$X_3(iter) = X_\delta(iter) + A_3.\ D_\delta(iter) \quad (17)$$

With the iteration iter, the obtained best positions $X_1(iter), X_2(iter)$ and $X_3(iter)$ were used to calculate the position $X(iter+1)$. A_1, A_2, and A_3 were calculated using Equation 9 and Equation 10 was used to calculate C_1, C_2, and C_3.

$$X(iter+1) = (X_1(iter) + X_2(iter) + X_3(iter))\ /3 \quad (18)$$

At last, the attacking process is achieved when the prey does not have an escape option and stops moving and is mathematically expressed by the linear fall in the value of α.

Improved Grey Wolf Optimisation (IGWO)

In GWO, α, β, and δ trapped in local optima search space due to mutual behaviour in search of the best solution and hence to get rid of this problem improved version of grey wolf has been introduced.[27] In this strategy, a new location has been generated for each wolf based on its neighbours and the new position of the generated candidate is denoted as X_D (iter+1) and can be calculated using Equation 19.

$$r_i(iter) = |X_i(iter) - X_G\ (iter+1)| \quad (19)$$

Where r(iter) is the radius determined using Euclidean distance (ED) between the current location X(iter) and the updated position X_G (iter+1) (calculated using Equation 18). Based on radius r(iter), neighbours $Ne_i(iter)$ of X_i (iter) can be defined using Equation 20.

$$Ne_i(iter) = \left\{X_j(iter) \middle| ED\left(X_i(iter), X_j(iter)\right) \le r_i(iter), \quad X_j(iter) \in PM\right\} \quad (20)$$

Where r(iter) is the radius determined using Euclidean distance (ED) between the current location X(iter) and the updated position X_G (iter+1) (calculated using Equation 18). Based on radius r(iter), neighbours $Ne_i(iter)$ of X_i (iter) can be defined using Equation 20.

$$X_{D,d}(iter+1) = X_{i,d}(iter) + rand.(X_{ne,d}(iter) - X_{rand,d}(iter)$$

Where PM is the population matrix of size N X D (N is the number of search agents of dimension D i.e., X_i(iter) = {x_{i1}, x_{i2}, x_{i3}, x_{i4}, ... x_{iD}) and $X_j(iter)$ is a randomly selected wolf from the population matrix PM. Multi-neighbor learning can be achieved after constructing the neighbor $Ne_i(iter)$ and expressed in Equation 21.

Where $X_{D,d}(iter+1)$ represents the position for d^{th} dimension and calculated using the d^{th} dimension of

$$X_i(iter+1) = \begin{cases} X_G(iter+1), & if\ fit(X_G) < fit(X_D) \\ X_D(iter+1) & otherwise \end{cases} \quad (22)$$

random neighbour $X_{ne,d}(iter) \in Ne_i(iter)$ and random wolf position $X_{rand,d}(iter) \in PM$ After performing multi-neighbour learning, the position of wolf at the next iteration has been updated using Equation 22. First, the best candidate is determined by comparing the fitness value of $fit(X_G)$ of $X_G(iter+1)$ and $fit(X_D)$ of $X_D(iter+1)$.

After the execution of this procedure for each iteration, undergoes until the maximum iteration value T reached and here it is 100, as a result minimum selected features were obtained. The working flowchart for IGWO-based FFDNN is shown in Figure 2.

To generalise the proposed model the performance of GWO and its improved version IGWO has been compared with PSO. Particle swarm optimisation is a swarm-based metaheuristic optimisation algorithm which simulates the flocking behaviour of swarms.[28]

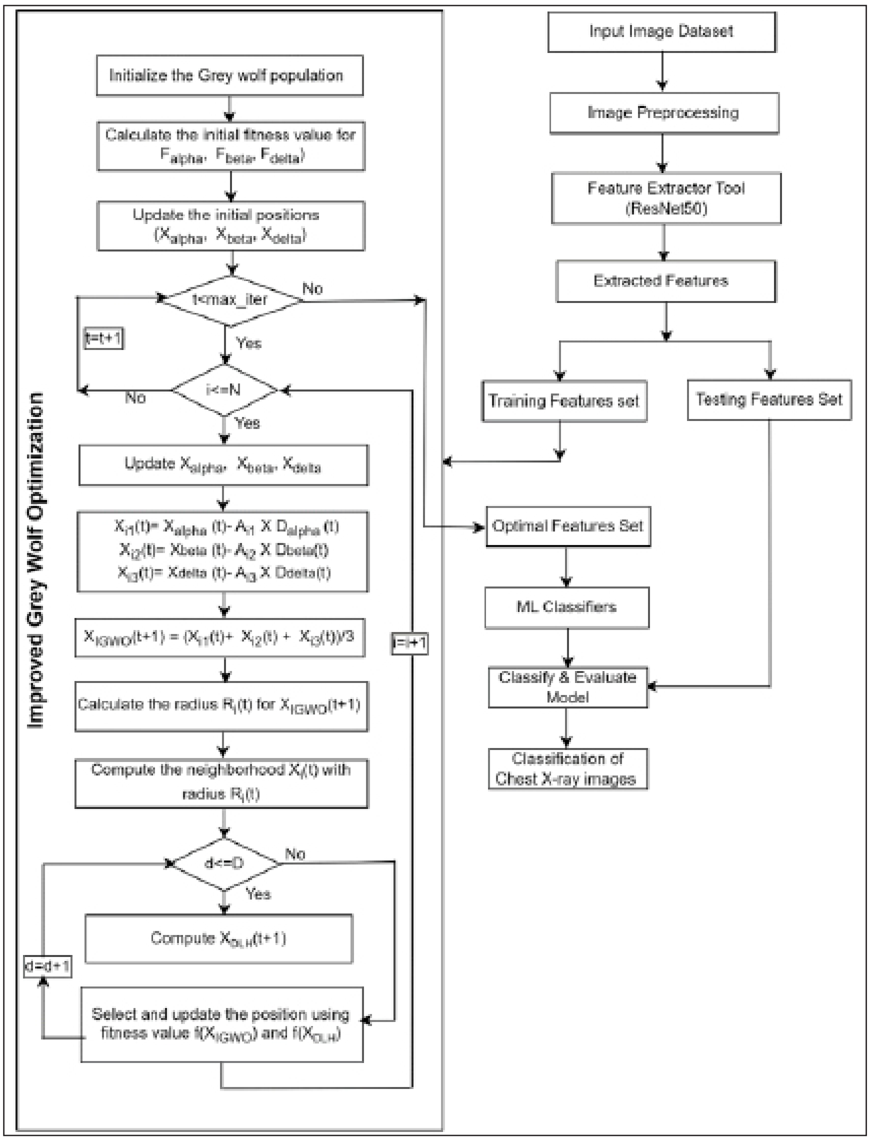

Figure 2.Flowchart for Proposed FFDNN with Improved Grey Wolf Optimisation Feature Selection Algorithm (IGWO)

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Machine Learning Classifier

This section discusses the final stage of the proposed FFDNN model, which is feature classification following the feature selection stage. To classify the selected features obtained from the previous stage, three ML classifiers have been implemented as follows:

- **Decision Tree (DT)[29]:** It is a tree-based structure where each node represents input image features and leaf nodes represent class labels. The classification process is facilitated by traversing the tree, with each node making decisions based on input features.
- **k-Nearest Neighbor (kNN)[30]:** A simple algorithm based on similarity with neighboring nodes, where Euclidean distance is widely used for measuring this similarity. The output class of a new input feature is the neighboring class with the highest similarity value.
- **Naive Bayes (NB)[31]:** A probability-based classifier that classifies features according to the largest posterior probability.
- **Linear Discriminant Analysis[32]:** Also based on Bayes' theorem, this method finds the probability of input features with respect to each class.
- **Support Vector Machine (SVM)[33]:** A nonlinear classifier commonly used for classification purposes. The kernel function, which defines the learning of the hyperplane (also called the decision boundary), classifies the input.

Proposed Work

This section illustrates the workflow of the proposed FFDNN model and the overall schema presented in Figure 3. The proposed FFDNN model has been divided into five stages as follows:

- Image preprocessing is the initial stage where the CXR images are enhanced using filtration, segmentation and enhancement techniques.
- Feature extraction process accomplished with the help of two pre-trained DNNs such as ResNet50 and MobileNetV2.
- Feature fusion enables the fusion of two extracted feature sets.
- The feature selection process implements the improved grey wolf optimisation for the selection of prominent and retrieval of optimal feature subsets.
- Feature classification is the last stage or the output stage of the proposed model where various machine learning classifiers classify the CXR images based on the output generated by the previous stage.

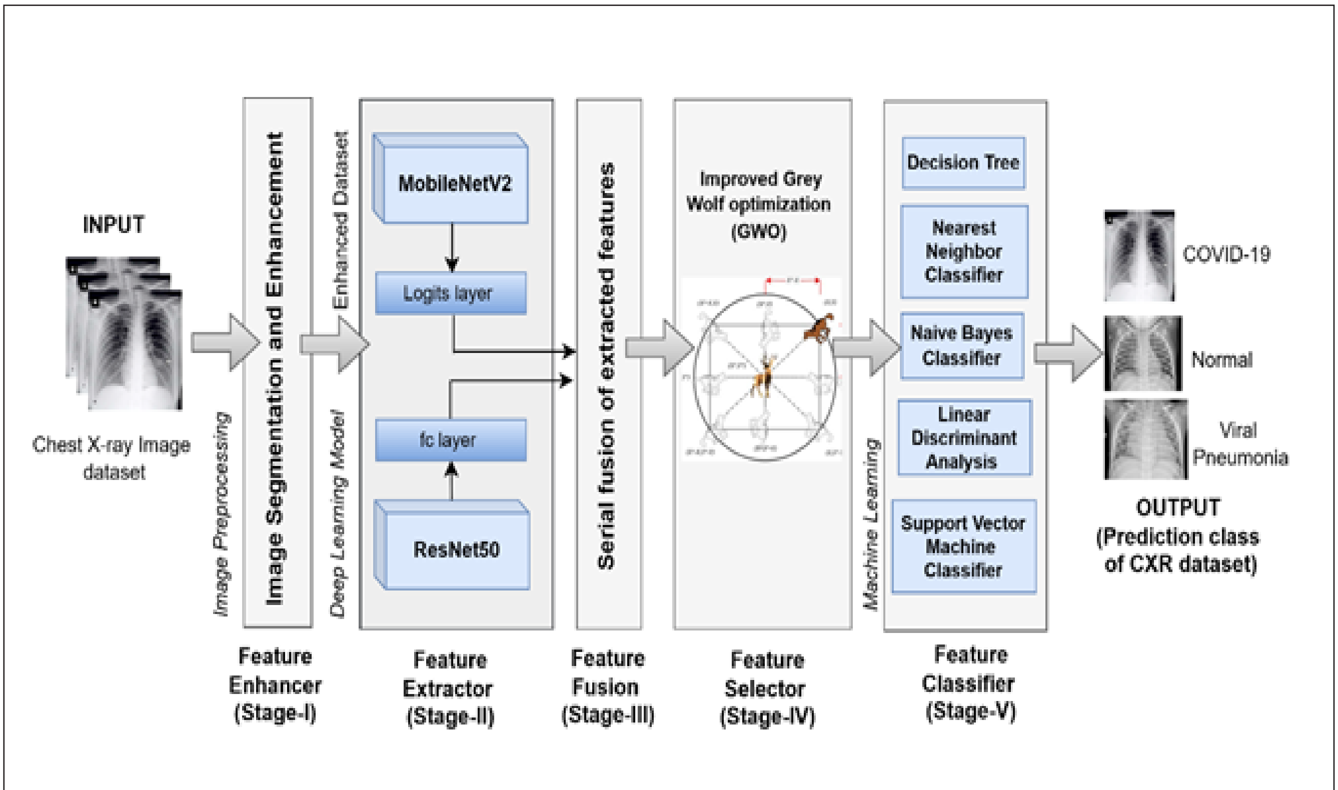

Figure 3.Overall Schema of Proposed FFDNN Model for Chest Disease Detection

Experiments and Its Findings

Experimental Setup and Datasets Used

The proposed metaheuristics-based DNN framework was validated using an original CXR (Chest X-rays) dataset. This multiclass dataset includes COVID-19, viral pneumonia, and normal CXR images. The dataset was collected from various sources,[34,35] ensuring it contains original, non-processed images. A balanced dataset with equal class representation was used to avoid overfitting. CXR images of COVID-19 patients show hyperlucent lung areas, normal images show typical chest structures, and viral pneumonia images show diffuse bilateral ground-glass opacities (GGO) and the sample image of each class has been shown in Figure 4. Enhanced CXR datasets were prepared using image preprocessing techniques as discussed in the section 3 (Image preprocessing techniques) .

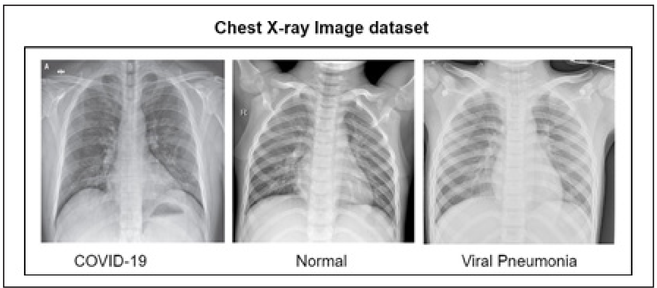

Figure 4.Sample CXR Images from CXR Dataset

Feature extractor models were trained on an enhanced CXR dataset using MATLAB 2023b as the development environment. Each of the CNN models was fine-tuned on the CXR dataset for 50 epochs with a batch size of 64. The Adam optimiser, with a learning rate of 0.0001, was utilised to minimise the cross-entropy loss during each epoch. After 50 epochs of training, the model achieving the maximum accuracy with minimum loss was considered ready for feature extraction. Further, the formulation of the proposed FFDNN has been performed based on the extracted features.

Performance Metrics

To quantify the performance of the proposed model, four metrics were computed: Accuracy (Acc.), Precision (Pre.), Recall (Re.), and F-score (F-Scr). These metrics are defined as follows:

- **True Positive (TP):** The model correctly identifies the actual class. For example, if the actual class is COVID-19 and the model classifies the input image as COVID-19, this is a TP.
- **False Positive (FP):** The model incorrectly identifies the class. For instance, if the actual class is Normal but the model classifies it as COVID-19, this is an FP.
- **True Negative (TN):** The model correctly identifies a class that is not present. For example, if the actual class is COVID-19 but the model classifies it as Normal, this is a TN.
- **False Negative (FN):** The model fails to identify the correct class. For instance, if the actual class is Normal and the model also classifies the input image as Normal, this is an FN.

These performance metrics are calculated using the Equations 23, 24, 25 and 26.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (23)$$

$$Precision = \frac{TP}{TP+FP} \quad (24)$$

$$Recall = \frac{TP}{TP+FN} \quad (25)$$

$$F-score = \frac{2TP}{2TP+FP+FN} \quad (26)$$

Experimentation Work

In this study, basically, three experiments have been performed to generalise the proposed FFDNN model. The enhanced CXR dataset is used for the training of two pre-trained DNNs i.e., ResNet50 and MobileNetV2. The extracted feature set undergoes the fusion operation and the fused features were considered for the classification purpose. Before the initiation of the classification process, the fused feature set has been optimised using the metaheuristic feature selection algorithms. On the basis of feature selection strategy, experimentation work has been classified into three groups and discussed in the further section:

Experiment 1: Proposed FFDNN based on the Feature Selection Particle Swarm Optimisation (PSO) Algorithm

Feature selection has been performed using PSO, the total number of features selected was 867 and the total time taken to execute was 58 secs. Based on the results shown in Table 1, SVM outperformed the other classifiers and obtained the maximum accuracy score of 98.47% comparatively more than the other classifiers: DT (85.93%), kNN (96.35), NB (94.19), LDA (95.41%) and SVM (98.47%). The selected PSO features also provide better performance in terms of precision (98.51%) and recall (98.47%) in the case of the SVM classifier.

Experiment 2: Proposed FFDNN based on the Feature Selection Original Grey Wolf Optimisation (GWO)

In the second experiment, the original GWO was used for the feature selection task where in total 735 features were selected. The time taken by GWO for the selection of features from the fused feature set was 41 secs which is comparatively lower than the execution time of PSO. The findings of the experiments (Table 1) have shown that SVM classifiers outperform the other classifiers ML classifiers. Maximum accuracy was obtained with the SVM classifier (97.78%) as compared to other classifiers: DT (85.32%), kNN (91.13%), NB (88.07%) and LDA (94.80%).

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Experiment 3: Proposed FFDNN based on the Feature Selection Dimension Learning Hunting-Based Grey Wolf Optimisation (IGWO)

In the third experiment, the feature selection process is accomplished with the help of Improved Grey Wolf Optimisation (IGWO). The total number of features selected in number is 823 and the time taken to optimise the fused feature set taken by the IGWO was 43 secs. From the findings of the experiment shown in Table 1, the same trend was followed by IGWO features where the highest accuracy was obtained with SVM (98.78%) as compared to other classifiers: DT (88.99%), kNN (97.55%), NB (94.19%) and LDA (96.33%). The confusion matrix obtained using the fused feature selected by IGWO and disparate ML classifiers has been shown in Figure 5.

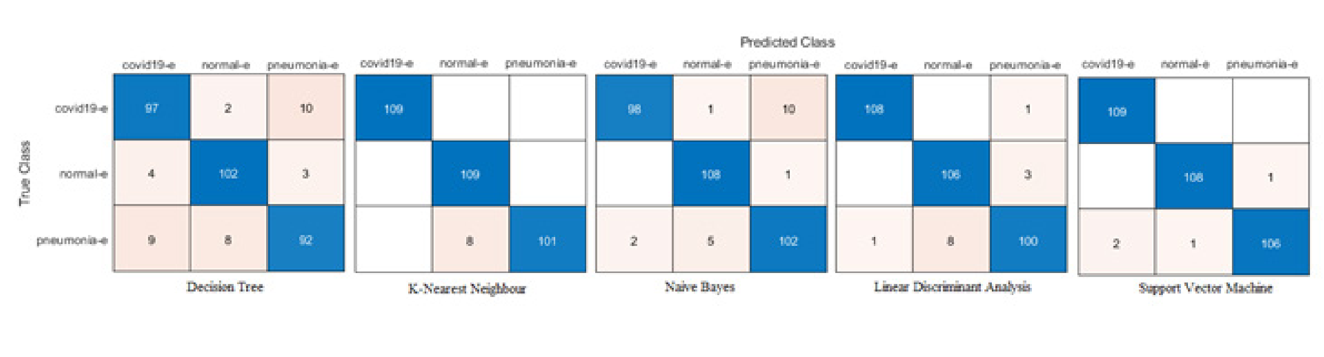

Figure 5.Confusion Matrix Obtained for Proposed FFDNN Model Based on IGWO using Enhanced CXR Dataset

Table 1.Results for the Various Performance Metrics for Proposed FFDNN

Metaheuristic Feature Selection Algorithm	No. of Features Selected	Time (in Secs) (Approximate Value)	Proposed Feature Fused DNN model with Fused ResNet50 and MobileNetV2 Features				
			Machine Learning Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F-Score (%)
PSO	867	58	DT	85.93	85.86	85.93	85.90
			kNN	96.35	96.36	96.35	96.35
			NB	94.19	94.57	94.19	94.38
			LDA	95.41	95.43	95.41	95.42
			SVM	98.47	98.51	98.47	98.49
GWO	735	41	DT	85.32	85.24	85.32	85.28
			kNN	91.13	91.22	91.13	91.18
			NB	88.07	88.82	85.63	86.32
			LDA	94.80	94.82	94.80	94.81
			SVM	97.78	97.66	97.76	97.71
IGWO	823	43	DT	88.99	88.96	89.00	88.98
			kNN	97.55	97.65	97.55	97.95
			NB	94.19	94.57	94.19	94.38
			LDA	96.33	96.36	96.33	96.34
			SVM	98.78	98.79	98.78	98.78

PSO: Particle Swarm Optimization
GWO: Grey Wolf Optimization
IGWO: Improved Grey Wolf Optimization

Discussion

In this study, major work is dedicated towards the feature selection process. Three metaheuristic-based feature selection algorithms i.e., particle swarm optimisation (PSO), Grey wolf optimisation (GWO) and the improved grey wolf optimisation (IGWO) have been implemented for the construction of the proposed FFDNN model. Based on the comparison shown in Figure 6, IGWO-selected features attained maximum classification accuracy than the other two feature selection algorithms. It has been observed from the experimentation results that GWO selects the least features and takes comparatively less time to execute, but the optimal feature set of GWO was not able to attain better classification accuracy as compared to IGWO.

On the other hand, the convergence curve shown in Figure 7 illustrates the convergence speed of PSO, GWO and IGWO. From the curve, it has been observed that IGWO attained a better convergence speed as compared to the other two algorithms. All three algorithms were executed for 100 iterations in total and the IGWO with more convergence speed was able to achieve better fitness value.

In addition to it, principal component analysis (PCA) has been also performed to analyse the feature selected using PSO, GWO and IGWO illustrated in Figure 8. Figure 8(c) shows the PCA analysis for the IGWO which shows densely populated features i.e., features with related characteristics have been selected, whereas the other Figures 8(a) and (b) show the sparsely connected features i.e., features with not much related characteristics.

The proposed FFDNN model based on IGWO as trained and experimented in experiment 3, also generates prominent results when applied to the Grad-CAM technique (a coloured visualisation technique). The outcome of Grad-CAM has been shown in Figure 9 which displays the affected regions of the lungs with a dark red colour. The output images were for COVID-19 and viral pneumonia and the results showed that blurred and whitish part i.e. infected region denoted by the red portion in Figure 9(a) case of COVID-19 and forpneumonia image Figure 9(b).

Figure 6.Comparison of Accuracy Obtained using Proposed Model with Different Metaheuristic Algorithms

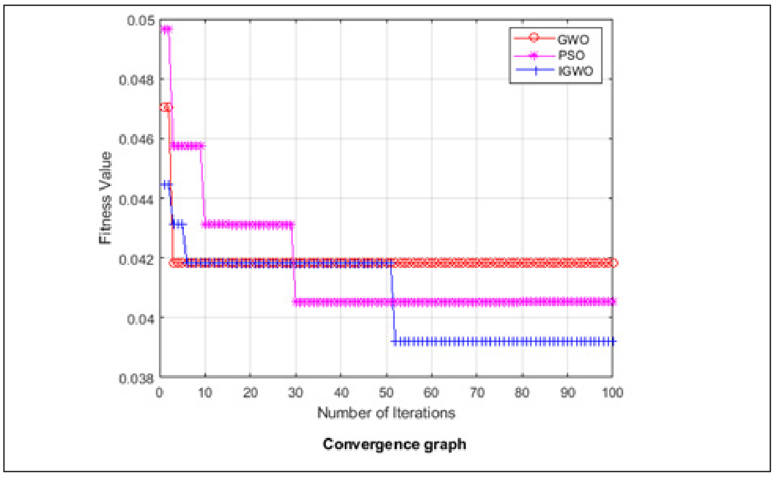

Figure 7.Convergence Curve for PSO, GWO and IGWO

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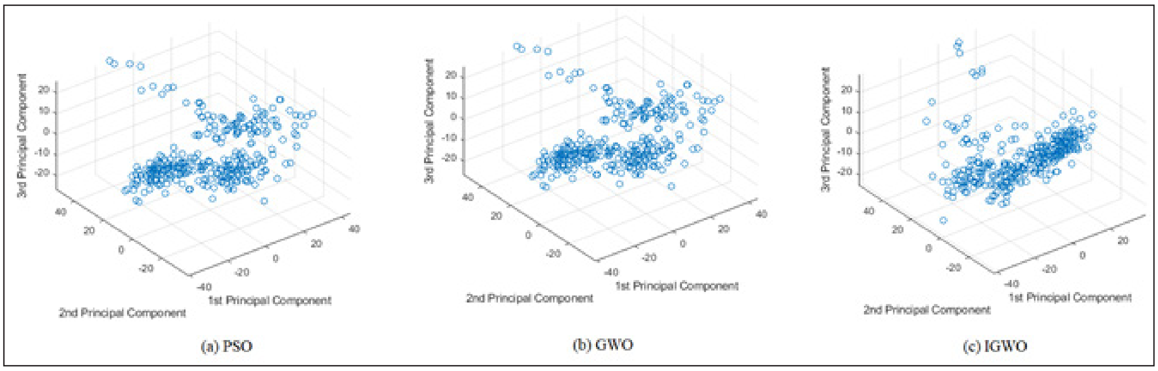

Figure 8.Principal Component Analysis for Selected Features

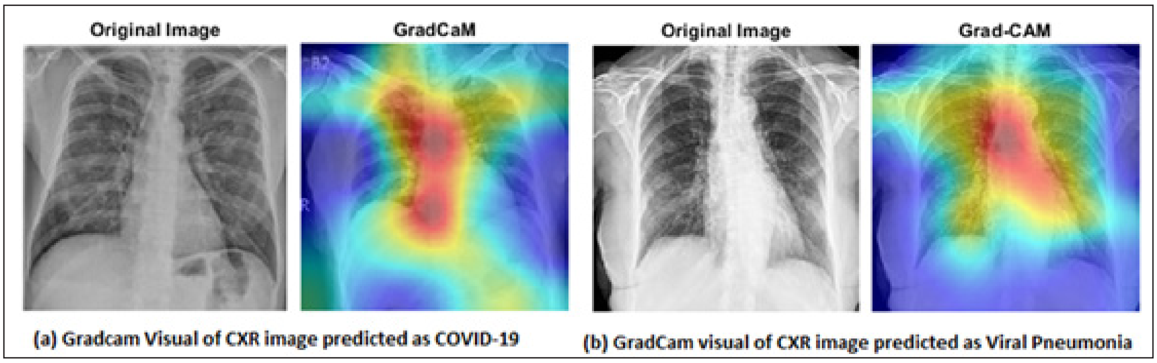

Figure 9.Grad-CAM Visualisation of CXR Images

Conclusion

In this study, the proposed model is based on feature fusion and feature selection methods. Experiments have been performed on multi-class CXR image dataset comprising COVID-19, viral pneumonia and normal images for the accurate detection of chest disease. In various performed experiments, the enhanced CXR image dataset using an efficient image preprocessing approach has been utilised. The proposed IGWO-based FFDNN provides the maximum accuracy (98.78%), precision (98.79%), recall (98.78%) and F-score (98.78%) for the classification of CXR images as COVID-19, viral pneumonia and normal. In the experiments, analysis of obtained features using PCA has also been performed and it has been proven that IGWO selects the best optimal solution as compared to the other two implemented feature selection algorithms. Adopted Grad-CAM approach outcomes claim the more interpretability and explainability of the proposed FFDNN model. In future, the experimented model can be utilised for other disease detection based on other medical imaging systems.

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